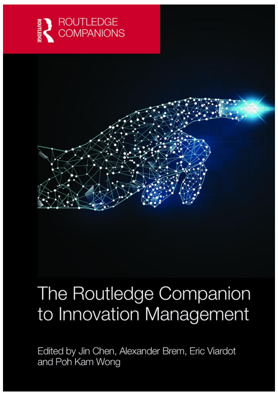

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Jin Chen, Alexander Brem, Eric Viardot, Poh Kam Wong

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Petra Ahrweiler
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INNOVATION MANAGEMENT SIMULATIONS USING AGENT-BASED MODELLING

Petra Ahrweiler

This chapter introduces the methodological approach of innovation management modelling following the advent of digitalisation, big data and computational simulation. It highlights how especially agent-based modelling has become an increasing appropriate innovation management tool for addressing the "what if" questions of organisational interventions, providing managers with insights from realistic scenario modelling in order to test and assess strategic options before the implementation phase. These new experimental methods are not only about identifying potential, chances and options of innovation management strategies but can also be used for avoiding undesirable outcomes in terms of an early-warning system. The computational methods are scalable: they apply to assessing innovation strategies of single firms, to clusters and to industry associations.

Starting from some general considerations of computational modelling in the social sciences, the chapter will introduce the field of agent-based modelling in innovation studies, will illustrate the potential of these new methodologies with five examples relevant to innovation managers from an existing simulation platform and will close with some recommendations for future utility in managerial practice.

Computational modelling in the social sciences

What is a simulation?

Simulations belong to the methodological repertoire of many scientific disciplines; they are used for multiple purposes, where the artificial representation of real-world systems on the computer for experimentation with parameter variations is only one (cf. Gilbert and Troitzsch, 2005).

> We wish to acquire knowledge about a target entity *T*. But *T* is not easy to study directly. So we proceed indirectly. Instead of *T* we construct another entity *M*, the "model", which is sufficiently similar to *T* that we are confident that some of what we learn about M will also be true of *T*. [. . .] At a moment in time the model has structure. With the passage of time the structure changes and that is behaviour. [. . .] Clearly we wish to know the behaviour of the model. How? We may set the model running (possibly in special sets of circumstances of our choice) and watch what it

> does. It is this that we refer to as "simulation" of the target. As will appear, if the model is a computational process within a computer, then simulation is a matter of executing that process and we speak of computer "simulation"
>
> *(Doran and Gilbert, 1994, p. 4f).*

There is a high degree of methodological and technical diversification in applying simulation across scientific fields: for the social sciences only, Gilbert and Troitzsch report in "Simulation for the Social Scientist" (2005) advantages and disadvantages of seven common simulation techniques illustrated by examples – among them the well-known equation-based system dynamic models, micro-simulations, queuing models from engineering, cellular automata and multi-agent systems. The latter rely on the approach of agent-based modelling (ABM).

What is ABM?

Agent-based modelling is used to model complex systems of interacting agents (cf. Gilbert, 2008; Epstein and Axtell, 1996; Bonabeau, 2001; North and Macal, 2007; Macal and North, 2009). Every agent in an ABM is an autonomous computer program with properties (variables, context of variables) and behaviours (algorithms, "rules"). Within multi-agent systems, various agent programmes interact with one another and with an environment represented in the model. An agent can be any unit with properties and behaviour ascribed by an observer, be it a human individual, collective actors such organisations, households or countries – everything with "agency" according to the research question under investigation (e.g. cars as agents in a traffic simulation).

With ABM, it can be observed how the structure and dynamics of a system emerge from the properties and behaviours of individual agents. This modelling approach is useful for analysing the relations between the micro and macro level of a system. It enables one to analyse the sequence of decisions leading to particular system behaviour as well as the feedback from changes at the system level for individual action.

There are ABM with simple, homogeneous agents: while every single agent has only few properties and is limited mostly to reactive behavioural options, interaction effects can, however, lead to quite complex system behaviour (an example is the famous Schelling model about segregation in American cities, cf. Schelling, 1971).

However, there are also models with more "intelligent"[1] agents in the wake of artificial intelligence approaches and the so-called "expert systems" featuring many heterogeneous agent types with a broad range of properties – among them anticipation, learning and individual dynamic knowledge bases – and a multitude of behavioural options (cf. concerning agent architectures Wooldridge, 2000; Balke and Gilbert, 2014). These heterogeneous complex agent types interact in dynamic environments.

This second approach is the best choice for representing human or organisation behaviour as realistic and detailed as possible – for example, while aiming at changing these strategies: only if we understand where and how properties and behaviours of agents change system features can we identify where changes at the agent level can lead to desired changes the system level. Though ABM are used for many purposes in a variety of disciplines, mainly the ones with "intelligent" agents are used for modelling complex human and social behaviour; in the social sciences, these are called "social simulations".

The relation between model and empirical data

To represent empirically observable actors and their behaviours in a simulation, agents need to be informed (calibrated) by empirical data. The better the data, the better the scientific theories and empirical knowledge about a certain phenomenon, and the better the simulation. In the simulation, software is used to build "artificial societies" (Doran and Gilbert, 1994) following empirical knowledge available for this world; social simulation crucially depends on sound social science theories and sufficient empirical social research (cf. for the relation between model and empirical reality Gilbert et al., 2018; Ahrweiler, 2017a, 2017b; Ahrweiler and Gilbert, 2005; Gilbert and Ahrweiler, 2009).

If there is enough similarity between empirical and computational models in terms of a qualitative correspondence (comparable dynamics, isomorphic structures), simulation experiments deserve the term "history-friendly":

> History-friendly models are formal models which aim to capture – in stylised form – qualitative theories about mechanisms and factors (. . .). They present empirical evidence and suggest powerful explanations. Usually these 'histories' (. . .) are so rich and complex that only a simulation model can capture (at least in part) the substance, above all when verbal explanations imply non-linear dynamics.
>
> *(Malerba, Nelson, Orsenigo, and Winter, 1999, pp. 3–4)*

The more empirical knowledge is used to calibrate a simulation, the more the computational worlds resemble the real-world context. The quality of a simulation can be measured by its "recognition value" for relevant stakeholders: recognising essential aspects of their daily experience settings in a simulation, stakeholders are confident in assessing the chance to learn from and with the simulation and in gaining useful knowledge and advice for interventions into the empirical system (cf., Ahrweiler and Gilbert, 2005).

For this, the calibrated model should be able to show some similarity to an empirical system at a defined point in time, reproducing the "history" of the system that has led to this state. Letting the simulation further run into the future following that same dynamics without any interventions within a "nothing ever changes" scenario (zero hypothesis) can then serve as a benchmark, as the baseline scenario, to conduct experiments with interventions.

Agent-based modelling in innovation studies

Innovation – the creation of new, technologically feasible, commercially realisable products, processes and organisational structures (Schumpeter, 1912; Fagerberg, Mowery, and Nelson, 2006) – is emerging from an ongoing interaction process of innovative organisations such as universities, research institutes, firms, government agencies, venture capitalists and others. These organisations generate and exchange knowledge, financial capital and other resources in networks of relationships, which are embedded in institutional frameworks on the local, regional, national and international level (cf. Pyka and Kueppers, 2003; Ahrweiler, 2010). Innovation is an emergent property from these interactions on the micro level – if the combination of actors and organisations, their compatible capabilities and their cooperative behaviours match. No equation will predict this match or warn of a mismatch beforehand.

Policy makers and managers of firms, universities and other participating organisations try to find out as much as possible about the structures and processes responsible for innovation. The managers want to know how to position their organisation optimally in these networks; the policy makers are concerned with the bird´s-eye perspective on the wellbeing and competitiveness of the overall network on the different policy levels. Those practitioners turn to science for insights into the mechanisms and processes producing these network structures and for guidance how to optimise their performance. What can scientists tell them?

Network analysis and ABM

To provide descriptions and explanations for why and how innovation happens, we need to analyse its structures and processes. The structural "hardware" consists of inter-organisational innovation networks. Innovation happens in networks. Ultimately, innovation performance is dependent on a complex interaction pattern at the micro level of innovative actors: it is "all about new knowledge, and networks are central to how it is produced and generated" (European Commission Workshop Report "Using Network Analysis to Assess Systemic Impacts of Research", March 2009). This is why we have to investigate the role of collaborative R&D arrangements in innovation. Since collaborative innovation has become the dominant and most promising way to produce high-quality output (Bozeman and Lee, 2005), these collaboration structures are the target for policy formation and evaluation.

Network analysis of innovation networks is one of the most vibrant interdisciplinary research activities we can observe in the moment. All parts of innovation networks have been of interest so far: there are studies concerning the binary combinations of involved actors (university-university, university-SME, university-MNE, SME-MNE, SME-SME, etc.) and about all possible links between these actors – R&D alliances (e.g. Siegel, Waldman, Atwater, and Link, 2003), spin-off activity (e.g. Smith and Ho, 2006), licencing (e.g. Thursby and Kemp, 2002) and all other possible link types. We find studies on university-industry links (cf. Ahrweiler, Pyka, and Gilbert, 2011) and all sorts of work on inter-firm networks (e.g. Schilling and Phelps, 2005; Porter, Whittington, and Powell, 2005).

Most of these studies have been carried out by economists or other social scientists. However, due to a rising interest in physics in the past ten years concerning complex networks, there has been much overlap and co-publication between physics and the social sciences from hybrid backgrounds such as econophysics or sociophysics.

> Research by physicists interested in networks has ranged widely from the cellular level, a network of chemicals connected by pathways of chemical reactions, to scientific collaboration networks, linked by co-authorships and co-citations, to the world-wide web, an immense virtual network of websites connected by hyperlinks.
>
> *(Powell, White, Koput, and Owen-Smith, 2005, p. 1132)*

Networks consisting of nodes and edges (or actors and relations, or units and links, etc.) are a ubiquitous phenomenon, where general insights apply to their topologies, structural properties and measures (Albert and Barábasi, 2002; Newman, 2003). Network analysis methods (Wasserman and Faust, 1994) have profited immensely from progress in physics concerning the field of graph theory and complex networks.

On a general level, innovation networks show features both, of so-called scale-free networks (Barábasi and Albert, 1999) and of small worlds (Watts and Strogatz, 1998; Watts, 1999). We have already studied some aspects concerning these two general features in more detail (Pyka, Ahrweiler, and Gilbert, 2009; Ahrweiler, Pyka, and Gilbert, 2011). This area connects to interesting debates, that is, whether strong ties – such as friendship, contracts, face-to-face interaction – or weak ties (such as access to information through loose contacts) are good for innovation (Granovetter, 1973; Uzzi, 1997; Burt, 1992, 2004; Ahuja, 2000; Walker, Kogut, and Shan, 1997; Verspagen and Duysters, 2004). What special network topologies do or do not do for knowledge flows has been widely discussed in this research area (Cowan, Jonard, and Zimmermann, 2007; Gloor, 2006; Sorensen, Rivkin, and Fleming, 2006) occupied both by physicists and social scientists, often in interdisciplinary co-authorship relations. Can we be satisfied with this contribution of science to describe and explain the innovation process?

There is an issue with some deficiencies of network analysis.

> Network analysis is a powerful tool to gather information (. . .) and can be used to define the properties of variables which may be useful for further investigation. At present, network analysts cannot give an understanding of the dynamic behaviour of the system; it only takes static snapshots of the databases and therefore lacks the time evolution perspectives (. . .). One may say that the system is far too complex to be modelled, but other scientific fields have shown that dealing with very large and complex systems may be possible with simplified models, capable of very good qualitative and semi-quantitative descriptions of those systems. This is true for economics, thermodynamics, epidemiology and even for the study of social behaviour.
>
> *(European Commission Workshop Report "Using Network Analysis to Assess Systemic Impacts of Research", March 2009, p. 15f)*

Network analysis focuses on structures and states. However, what happens between the states we capture (causal mechanisms/processes producing the structures) and states we analyse? What about innovation behaviour? What about the "production algorithms" for the structures we observe? Network analysis does not address the "agency dimension" of innovation networks (cf. Ahrweiler, 2010) where innovative individuals and/or organisations move in an action space, which is co-evolving with them. The agency dimension, that is, the possibility of actors to move intentionally in the action space, provides the processes and mechanisms for network formation and development: it is what actors do and do not do that matters. Starting to address this dimension by network analysis would imply more complex node properties and/or more heterogeneous link types for each node – be they people or organisations. A real-world actor moves in an action space, which consists of many dimensions (actors are even permanently inventing, constructing, anticipating, changing, developing, etc. their action space, not just moving around in a given world). The notion of "actor" is tale-telling in this respect: it is originally used for being on the stage in a theatre performing multiple roles. Actors in different roles would need rich node descriptions concerning properties, behaviours and states and/or a richer link structure, which manifests what the actor does in relation to others. In network analyses, instead, the dimensions of nodes are rather limited – if an organisation is part of an EU R&D network under investigation, its relevant property is that it is doing funded EU research with other organisations – whatever roles it performs besides does not matter, nor how these different roles provide feedback on the respective R&D network tie. In the moment, multi-level networks are a research challenge for people interested in complex networks.

Furthermore, network analysis does not capture the particularities of knowledge generation and distribution. Network analyses deal with knowledge as "flow substance" in a way which does not discriminate knowledge very much from what flows in other types of networks, such as energy or information. It is structure that matters – not the particularities of the flow substance (i.e. knowledge). One consequence of this focus is that most network analyses address knowledge/innovation diffusion issues but do not provide many insights on the processes of the emergence of the new (knowledge generation, innovation). However, this is exactly what is required to describe innovation processes adequately and help practitioners to deal with their problems.

Adding a procedural perspective to the analyses will provide important insights. Here, an inter-disciplinary, or, even better, a trans-disciplinary, initiative offers a conceptual framework to help. This is complexity science (Bar-Yam, 1997, 2004; Braha, Minai, and Bar-Yam, 2008; Casti, 1995; Flake, 1999; Stewart, 1989; Waldrop, 1992). Business studies and management science have already taken this up: areas such as strategic organisational design (e.g. Anderson, 1999; Brown and Eisenhardt, 1998; Dooley and van de Ven, 1999; Eisenhardt and Bhatia, 2002; McKelvey, 1999) and innovation management (e.g. Buijs, 2003; Chiva-Gomez, 2004; Cunha and Comes, 2003) have applied key concepts of complexity science to innovation issues addressing procedural aspects and qualitative properties of knowledge and agency, rather than merely quantitative features of certain structures.

Complexity science perspectives locate innovation processes in turbulent environments with high uncertainty and ambiguity: they assign to innovation processes characteristics such as multi-scale dynamics with high contingency and non-linearity, emergence, pattern formation, path dependency, recursive closure and self-organisation (Frenken, 2006; Lane, van der Leeuw, Pumain, and West, 2009). Such concepts (cf. Arthur, 1989, 1998) are of rising importance to describe and explain innovation processes, building on mathematical concepts for systems analysis originating from physics and engineering science (Gell-Mann, 1994; Kauffman, 1993, 1995; Prigogine and Stengers, 1984; Holland, 1995). Representing knowledge flows in innovation networks means to follow agents who invent, learn and interact. To capture the dynamics of these learning activities, agent-based modelling is increasingly applied for research (see e.g. Windrum, 2007; Gilbert, Ahrweiler, and Pyka, 2010).

ABM in innovation studies of computational economics

The advantages of using ABM in innovation studies have been confirmed by a growing number of models (cf. Ahrweiler, 2010, pp. 233–315). These models implement, for example, the interaction of knowledge and actors, of outputs and organisations, of network formation and evolution. They simulate the interdependencies of existing innovation policies and funding strategies, of future innovation policy scenarios and alternative technology paths to improve innovation performance. ABM in innovation studies gain more and more prominence, where simulation is increasingly used for innovation policy advice and management support (cf. Dawid and Neugart, 2011). Policy is already very interested in innovation studies in general due to the important role of innovation for economy and society (cf. Martin, 2012); this is increased by the options of ABM to provide answers to what-if questions and ex-ante evaluation for policy interventions (Ahrweiler, Gilbert, and Pyka, 2016).

Herbert Dawid (2006) investigates the potential of the agent-based computational economics (ACE; cf. Tesfatsion, 2003, 2006) approach for the analysis of innovation processes. One of his conclusions is that ABM is particularly appropriate for studying genuine properties of innovation such as the strong substantive uncertainty involved or the special characteristics of knowledge. Furthermore, ABM have proven to be quite successful in explaining sets of stylised facts in innovation which could not be explained by alternative approaches. Dawid also presents the results of a systematic survey on ACE models of innovation and discusses their contribution to the field.

Central insights from an evolutionary economics approach are introduced and models categorised according to their contributions to them. For example, the heterogeneity of agents and their innovation strategies are the focus of models by Dawid, Reimann, and Bullnheimer (2001), Dawid and Reimann (2003, 2004), as well as Llerena and Oltra (2002). Uncertainty of innovation processes is central in models of Birchenhall (1995), Windrum and Birchenhall (1998), Cooper (2000), Ebeling, Molgedey, and Reimann (2000), Yildizoglu (2001), Natter et al. (2001) or Silverberg and Verspagen (2005). Following the early model of Grabowski and

Vernon (1987) for micro-founded insights into the structure of industries Dawid lists models such as Dosi, Marsili, Orsenigo, and Salvatore (1995); Klepper (1996); Winter, Kaniowski, and Dosi (2000, 2003); Malerba, Nelson, Orsenigo, and Winter (1999, 2001); or Malerba and Orsenigo (2002).

Many contributions are listed under the heading "agent-based economic growth model with a focus on innovation" (Dawid, 2006, p. 26) to combine a strong micro-foundation with the reproduction of a number of stylised facts about economic growth. Among them are Silverberg and Verspagen (1994, 1995, 1996); Chiaromonte and Dosi (1993); Chiaromonte, Dosi, and Orsenigo (1993); Kwasnicki (2001); Fagiolo and Dosi (2003); Dosi, Fabiani, Aversi, and Meacci (1994); and Dosi, Marsili, Orsenigo, and Salvatore (1995). More detailed reviews for this field can be found in Silverberg and Verspagen (2005), Pyka and Fagiolo (2005) or Windrum (2007). The analysis of Dawid suggests that we can expect a strong structuring effect of relevant author communities from different disciplines and contexts for shaping the field.

Furthermore, Dawid emphasises the role of knowledge as the "most important input factor for the 'production' of innovation" (Dawid, 2006, p. 1235f). In his section about knowledge accumulation, knowledge structures and spillovers, Dawid introduces knowledge stock with units of knowledge and knowledge structures as the most relevant targets for knowledge representation, where "the stock of knowledge of a firm is not uniform and has a lot of structure" (Dawid, 2006, p. 1236). Representation can be done by a single variable, where "knowledge accumulation is treated either implicitly, by assuming that all current knowledge is embodied in the technology currently used, or by considering a simple R&D stock variable, which is increased by investments over time" (Dawid, 2006, p. 15), or a more complex construct such as a vector in a multi-dimensional space. In the latter case, "models of knowledge are represented with abstract vectors made of topics with a more or less complicated structure" (Barreteau and Le Page, 2011, p. 3.4). Though Dawid (2006) only lists four models in this section of his review: Cantner and Pyka (1998); Ballot and Taymaz (1997, 1999), Gilbert, Pyka, and Ahrweiler (2001) and Meagher and Rogers (2004), his discussion suggests that we can expect a strong structuring effect of different approaches to knowledge modelling for shaping the field.

Central issues in simulating innovation

This expectation is strongly supported by the recent overview and critical discussion of existing computational innovation models with a focus on ABM provided by the book by Christopher Watts and Nigel Gilbert (Watts and Gilbert, 2014). The book reviews model types, general model requirements, techniques and prototypes, rather than aiming at a review of the existing publication landscape. In their chapter on technological evolution and innovation networks, Watts and Gilbert (2014) compare ten existing models for their representations of knowledge, technologies, strategies or rules (p. 232). For most of them, they find a bit string knowledge representation (March, 1991; Lazer and Friedman, 2007; Axelrod, 1997; Lindgren, 1992), for others a representation through cell locations/states in a grid (Silverberg and Verspagen, 2005, 2007), numerical variables (Cowan, Jonard, and Zimmermann, 2007), combinations of logical gates (Arthur and Polak, 2006) or multi-dimensional vectors (Ahrweiler, Gilbert, and Pyka, 2004). Watts and Gilbert discuss the advantages and limitations of these different modes of knowledge representation in detail (pp. 192–238). In this chapter, models are described, which incorporate generation, diffusion and impact of innovation.

Previous chapters discuss models that only cover one or two of these three processes, for example, diffusion models (cf. Rogers, 2003, Abrahamson and Rosenkopf, 1997, Valente, 1996). Of course, knowledge modelling is also crucial for issues around innovation diffusion:

> [R]epresentation of knowledge flows across this boundary is still a difficult question. Several works have already tried to represent pieces of knowledge as specific entities in the modelling of a system and its dynamics. The representation of knowledge flow processes has been developed in the field of innovation diffusions in the context of corporate businesses.
>
> *(Barreteau and Le Page, 2011, p. 3.1)*

Here, another relevant author community comes to attention: the scholars from business studies concerned with knowledge management issues. Their influence will also contribute to the structuring of the field.

Here comes yet another important driver for the field: "ABM in innovation studies". As Watts and Gilbert (2014) state,

> [O]rganisations need to consider their markets and their competitors' behaviour. They also need to reflect on their own sources of innovation and learning, and be prepared to adjust those sources in response to changes in the market (. . .) computer simulation models of innovation within organisations have demonstrated how problem-solving and learning performance is sensitive to a variety of factors.
>
> *(Watts and Gilbert, 2014, p. 132)*

As can be checked, for example, for the Special Issue "Agent-based Modelling of Innovation Diffusion" of the *Journal of Product Innovation Management* (edited by Garcia and Jager, 2011), most papers on ABM in innovation studies end up with "managerial implications" (Broekhuizen, Delre, and Torres, 2011, p. 214). These statements suggest that the intent of their model is "to provide practical insights (. . .) to governmental policymakers" (Zhang, Gensler, and Garcia, 2011, p. 164) or that their model is "an effective means for making useful (. . .) policies and managing the processes (. . .) under different policy scenarios" (Zhang and Nuttall, 2011, p. 185). We can expect a strong structuring effect from this orientation towards management and policy practice for shaping the field.

In the wake of combining innovation generation and innovation diffusion, these authors introduce important concepts for knowledge modelling to the field, for example, the exploration-exploitation dichotomy, which Watts and Gilbert (2014) discuss in their Chapter 4 in detail: March (1991) uses this distinction in his ABM on organisational learning (Argyris and Schön, 1996), which became one of the influential models in the field and was revisited, for example, by Rodan (2005) and further interpreted by Fagiolo and Dosi (2003). We can expect to find more of such little communities and model trajectories while assessing the publication database. As Watts and Gilbert state: "March's distinction between exploration and exploitation has been much cited, and his computer model has seen some attempts at replication and extensions. (A special issue on March's paper appeared in the Academy of Management Journal 49/4, 2006)" (Watts and Gilbert, 2014, p. 104). Models of organisational learning concern innovation within organisations, which suggests that we can expect not only a strong community looking at systemic interactions between technology, economy and society at large (see earlier) but also an at least similar-sized community looking at innovation on the firm level from a management and business studies perspective. Of course, there are all kind of brokers and bridges between these two communities around the topic of learning and spillovers such as Pyka and Cantner (1998) or Pyka, Ahrweiler, and Gilbert (2009).

Another dichotomy introduced by Watts and Gilbert (2014) in the context of learning and incremental vs. radical innovation is relevant for modelling learning and innovation by searching a knowledge/technology landscape looking for peaks as areas of novelty and success – either in small step changes (incremental) or by jumps into completely different areas of the landscape (radical). Here, models are introduced in the wake of Kauffman's NK fitness landscape (Kauffman, 1995) such as Frenken (2001, 2006) or Lazer and Friedman (2007). Innovation generation has been dealt with by various models, some with a stronger focus on the knowledge side, that is, the evolution of new technologies (Silverberg and Verspagen, 2005, 2007), others with a focus on the actor side, that is, the emergence of innovation networks (Cowan, Jonard, and Zimmermann, 2007).

In summary, there seem to be heterogeneous scientific communities involved with different reasons for using ABM for analysing innovation. In the general innovation literature, there are two poles,

> one of which focuses on innovation in firms, and is popular with scholars in business and management, the other emphasises the role played by technology and innovation in economic and social change more generally. The latter is particularly influential among scholars with a background in economics and other social sciences.
>
> *(Fagerberg, Fosaas, and Sapprasert, 2012, p. 1141)*

Another central issue again centres around the requirements for knowledge modelling in the field. In innovation, new knowledge (scientific discoveries, emergent technologies and disruptive innovations) is involved as the main component and the radical game-changer (cf. Bhupatiraju, Nomaler, Triulzi, and Verspagen, 2012; Loasby, 1999). Knowledge dynamics, that is, how knowledge is generated, shared, distributed, learnt, combined and recombined, forgotten or applied, are the key dynamics on the micro level, which produce innovation performance on the system level measurable using knowledge and innovation output indicators for assessing and tuning desirable system outcomes. It seems as if the conceptual landscape is mainly structured by thematic contributions to issues of knowledge representation.

The last issue we want to follow up on from insights of the previous review literature is that there seems to be a specific dedication of the field to produce impact outside academia. Many papers end up with policy recommendations or management advice stemming from research results. Of course, innovation plays an important role for economy and society, and ABM can provide answers to what-if questions and ex-ante evaluation for policy and management interventions. Models seem to be increasingly used for innovation policy advice and management support. Again, knowledge modelling seems to be a critical issue here. We might assume that the more policy-driven a model is, the stronger the focus on realistic knowledge representation, because knowledge is a key driver for innovation and the first target for policy and management interventions. Therefore, the quality of decision support models might crucially depend on how knowledge is represented.

Firm perspectives on innovation modelling with ABM

For a firm, it is always a risky enterprise to change the innovation strategy: changes can concern technological focus or prioritisation, cooperation or partner choice mechanisms, investment or funding strategies, tech transfer models, entrepreneurship strategy, location, network position and many other dimensions. In most cases, these changes concern highly specialised organisations acting in a complex environment characterised by many actors, competition, resource scarcity, etc. Pressure to be successful is usually high. Change would mean to leave or at least to question the current profile of the organisation and the – possibly very successful – status quo. It often implies a redistribution of financial and human resources and attention; existing priorities have to be changed or reduced for new ones.

Change will only be fully justified by future success, which is, by its nature, uncertain as an outcome, and therefore risky. How to reduce uncertainty and risk by increasing the predictive power of ex-ante evaluation concerning intended changes? Innovation managers need complexity-adapted tools to support their change decisions: the true uncertainty (Knight, 1921) of knowledge availability, access and transfer; of technology absorption; of financial risk; of regulatory barriers and institutional impediments; of market access and profitability counteracts all predictability (Pyka and Ahrweiler, 2008). The characteristics of firm innovation in complex social systems – be it for big multinationals (cf. Narula and Michel, 2010; Heidenreich, Barmeyer, and Koschatzky, 2010) or for small and medium businesses (cf. Asheim, 2010) – leave much remaining uncertainty on the shoulders of innovation managers.

Agent-based modelling of innovation processes can advise innovation management in a way which makes innovation indeed computable (cf. "The Economy Needs Agent-Based Modelling", *Nature* 460, 06.08.2009, p. 685f). An adequate ABM of the innovation landscape will not only allow one to investigate micro-macro links for innovation performance on the system level but will also allow for tracking single agents such as firms of a certain type through the simulation to assess how successful they are with what (combination of) strategies and with what type of managerial interventions. This way, it will be possible to evaluate where a firm sits with its profit model, with its products, with its service and engagement model, etc., in comparison to others and how it can navigate best to improve its position in the innovation ecosystem. In the following, five examples for strategically relevant innovation management questions have been chosen to illustrate the application context of ABM for firm perspectives: they stem from studies using the open-source Creative Commons simulation platform SKIN (cf. Watts and Gilbert, 2014, pp. 228–237).

The SKIN model

The agent-based simulation platform SKIN (acronym for *S*imulating *K*nowledge Dynamics in *I*nnovation *N*etworks) works with heterogeneous, "intelligent" and complex agent types, which act and interact in a computational world resembling the empirical world as much as possible. There is a close relationship between theory, empirical data and simulation. Due to this, SKIN claims to be relevant for providing innovation management advice. SKIN reproduces the research and innovation worlds of empirical actors on the computer. By calibrating the model with empirical data sets, it allows realistic and detailed experiments to answer "what if" questions of innovation management.

The SKIN model is concerned with simulating knowledge profiles, science and research landscapes and innovation networks on different scales. The "basic SKIN model" has been presented elsewhere (cf. Pyka, Gilbert, and Ahrweiler, 2007; Gilbert, Ahrweiler, and Pyka, 2007; Ahrweiler, Gilbert, and Pyka, 2011). On its most general level, SKIN is an ABM with knowledge-intensive organisations as agents, which try to produce new basic or applied knowledge and/or which try to produce new products and processes via innovation. Agents are located in permanently changing, complex social environments where their efforts need to find approval, for example, in the market if they target innovation, or in the scientific community if they try to publish their research results.

SKIN agents are knowledge-intensive, learning organisations. Each agent owns an individual dynamic knowledge profile. In the model, an agent's individual knowledge base – a vector in a multi-dimensional space – is called its "kene" (Gilbert, 1997), which the agent uses as the source and object for its research and innovation activities. The abstract knowledge profile can be "fed" (i.e. calibrated or informed) by empirical data. "Data points" are "units of knowledge" (e.g. core competences, capabilities, codified and tacit knowledge, explicit and implicit knowledge) which are produced, used and made available.

For example, we can directly work here with publication and patent or other source data for specific actors and contexts. Using methods from bibliometrics, scientometrics, patent analysis, etc., structural knowledge profiles of organisations can be collected, analysed and evaluated. Interpretative social science can furthermore contribute to shedding light on knowledge profiles by making the context of meaning and the connectivity to actions accessible and "understandable" via interviews with actors, case studies and document/discourse analysis. Using this modelling approach, SKIN represents and simulates the knowledge profiles of organisations active in research and innovation where, in aggregation and extrapolation, knowledge profiles of countries, regions, municipalities and clusters can be reconstructed and simulated. Simulating knowledge profiles belongs to every SKIN application. The kene is dynamic: an agent can learn – either alone by incremental or radical research, or together with other agents by exchanging and improving knowledge in partnerships and networks (following learning mechanisms from Organisational Learning according to March and Olsen, 1975; Argyris and Schön, 1996).

Within these collaborative arrangements, SKIN agents have a large number of strategies and mechanisms available, for example, to choose partners (following empirical partner choice mechanisms as elaborated by Powell, White, Koput, and Owen-Smith, 2005), to engage in partnerships, to initiate knowledge exchange, to generate collaborative knowledge outputs or to distribute innovation rewards. These interactions and the resulting social structures can be calibrated by empirical data as well. Information on the structures and dynamics of the science and research landscape on the actor and system level is broadly provided for countries, regions, sectors and clusters. "Data points" are actors, interactions and networks in research and innovation. Social network analysis (SNA) is a common tool to analyse this type of empirical data identifying and visualising central actors (hubs), clusters, the position and role of new entries in the research and innovation landscape, etc. However, it only addresses the structural aspects of the science and research landscape. Actors, processes and causal chains producing these network structures are in between "snapshots" of two network states following each other. Information on actors, their expectations, objectives, competences, strategies, cooperation behaviour, etc., and about their action contexts, the processes, cultures and institutional frameworks they are embedded in must be made transparent, accessible and "understandable" again with the help of complementary qualitative methods such as interviews with actors, case studies and document or discourse analysis.

Summarising, agents in any SKIN application interact on both the knowledge level and the social level. Both levels are inter-linked in many different ways. SKIN is all about actors, knowledge and networks. This general architecture is quite flexible, which is why the SKIN model has been called a "platform" (cf. Ahrweiler, Pyka, and Gilbert, 2014). It features applications as different as modelling the Vienna biotech cluster (Korber and Paier, 2014), the simulation of Irish university-industry networks (Ahrweiler, Pyka, and Gilbert, 2011) and also the ex-ante evaluation of EU-funded research projects and the research landscape they produce (Ahrweiler, Schilperoord, Pyka, and Gilbert, 2015).

Five examples: SKIN for innovation management

Are R&D alliances and partnerships better than go-it-alone strategies?

This question is quite familiar in innovation management: it addresses the benefits and worries around open innovation (Chesbrough, 2003). The SKIN application investigating this question concerned the biotechnology-based pharmaceutical industry in Europe as a sector *par excellence* of a knowledge-intensive industry. The simulation was about assessing the effects of different learning activities of firms in this sector (go-it-alone strategies such as incremental and radical learning, as well as learning through R&D partnerships and innovation networks). The simulation tested the trade-off between go-it-alone strategies and different cooperation strategies and evaluated what combination of strategies worked best for which type of agent.

The results of this application (Gilbert, Ahrweiler, and Pyka, 2007, 2010; Ahrweiler, Gilbert, and Pyka, 2006) were closely observed by a large multi-national corporation in the UK pharma industry, which at that point in time was concentrating on go-it-alone strategies, because this company's management was about to decide on the future cooperation and embeddedness strategies of their enterprise within the surrounding industry. Tracking the performance of an agent through the simulation that had similar properties as the company but applied different combinations of learning and cooperation strategies provided interesting policy and management insights in how to navigate in complex innovation networks and how to improve its position in the network to exploit its resources to the best advantage. For this company, which was and still is a big player in the field, the simulation showed good results for their then prevalent go-it-alone strategies but demonstrated better results for specific combinations of learning strategies, including cooperation.

Is including SME in big-scale technological innovation projects indeed beneficial?

The European Commission was expecting to spend around €77 billion on research and innovation through its Horizon 2020 programme between 2014 and 2020. It is the successor to the previous, rather smaller programme, called Framework 7. When Horizon 2020 was being designed, the Commission wanted to understand how the rules for Framework 7 could be adapted for Horizon 2020 to optimise it for current policy goals, such as increasing the involvement of small and medium enterprises (SMEs).

The application INFSO-SKIN was built to evaluate possible funding policies. The model was set up to reproduce the funding rules, the funded organisations and projects and the resulting network structures of the Framework 7 programme. Among the tested questions was what would happen if the Commission would manage to increase SME participation (Ahrweiler, Schilperoord, Pyka, and Gilbert, 2015).

The objective to integrate innovative research-intensive SME in EU-funded research is a long-standing one and highly motivated:

> Through their flexibility and agility, SMEs play a pivotal role in developing novel products and services. Outstanding and fast growing SMEs have the potential to transform the structure of Europe's economy by growing into tomorrow's multinational companies (. . .) although particular attention has been paid to increasing SME involvement throughout FP7, SMEs are still finding it challenging to participate.
>
> *(Green Paper on a Common Strategic Framework for EU Research and Innovation Funding: Analysis of public consultation, 2011, S. 10)*

The European Commission (EC) had already issued a few studies to find out about the reasons for the "policy failure", why EU funding was not as attractive as expected for SMEs and why the measures taken had not been as successful as expected. However, a discussion had also started among the policy analysts, whether the policy efforts and costly incentive structures to draw SMEs into EU research were really worthwhile and would pay off in the way expected.

Is including SME in big-scale technological innovation projects indeed beneficial? This was not only an interesting question for EU policy but would also be of interest for MNE or industry associations. The related simulation experiments using INFSO-SKIN started with considerably more research-intensive and highly specialised SMEs in the starting population than could be seen in the empirical distribution. The simulation showed that these "additional" SME overproportionally participated in proposals and, especially, in successful project consortia. Furthermore, they had positive effects on knowledge and network parameters. This result supported the SME policy advocates in the EC stakeholder group who represented the Green Paper position and argued against the critics of these policies within the group.

Do innovation projects need "new actors" such as civil society organisations to become responsive to societal values and act responsible in innovation?

This is another well-known debate in innovation management: What are the advantages of user-driven innovation (von Hippel, 2006)? The SKIN application GREAT-SKIN (Ahrweiler, 2016) was created to test some assumptions of the approach to "responsible research and innovation" (RRI).

> Responsible research and innovation is an approach that anticipates and assesses potential implications and societal expectations with regard to research and innovation, with the aim to foster the design of inclusive and sustainable research and innovation. Responsible Research and Innovation (RRI) implies that societal actors (researchers, citizens, policymakers, business, third sector organisations, etc.) work together during the whole research and innovation process in order to better align both the process and its outcomes with the values, needs and expectations of society. In practice, RRI is implemented as a package that includes multi-actor and public engagement in research and innovation, enabling easier access to scientific results, the take up of gender and ethics in the research and innovation content and process, and formal and informal science education.
>
> *(http://ec.europa.eu/programmes/horizon2020/en/h2020-section/responsible-research-innovation)*

In particular, the involvement of civil society on the individual level as interested citizens and on the organisational level of civil society organisations (CSOs) is supposed to change the research and innovation system towards RRI functions by anticipation and foresight (e.g. to prevent harmful consequences); by permanent accompanying reflection concerning responsibility aspects in research and innovation; by discursive, deliberative and participative opinion formation and decision making embedded in value discussions; and by responsive behaviour of all participants. Quality and accountability of research results will be assigned to the research and innovation process, and especially to the producers (i.e. the societal actors participating in research and innovation).

Empirical findings had indicated, however, that other agent types (universities, research organisations, SMEs, MNEs, etc.) were likewise active in promoting RRI in European research and innovation: these other agent types carried RRI capabilities as well and were major players for RRI diffusion. CSOs, in turn, were involved in projects not only as society representatives but also – and sometimes rather – for their domain and knowledge expertise in specific areas of research. The empirical findings indicated this with data and correlations. They did not, however, offer the full causal explanation, because, of course, in empirical reality it is impossible to observe processes such as "RRI learning" of and between different agent types; it is impossible to observe and measure knowledge exchange, knowledge flows, knowledge diffusion, etc.

This has been the task of the GREAT-SKIN simulation model. It allowed checking for the empirical "un-observables": in a simulation, it is possible to observe and measure "RRI capabilities" of agent types and "RRI learning/diffusion" between them. Simulation experiments were conducted that changed the level of CSOs' involvement in projects. They showed that the number, identity and role of CSOs are *not critical* to the simulation outcomes. Diffusion patterns of RRI showed that special RRI capabilities of CSOs are increasingly adopted and then contributed by other agent types and via the same learning mechanisms, CSOs increasingly adopt and then contribute scientific capabilities. All in all, simulation results confirmed and explained the insights from the empirical data sets, that is, that CSO are not more active than industry to implement institutional mechanisms for anticipation, reflection, deliberation and responsiveness, even hinting that SMEs were the front runners in that activity.

What are the benefits of multi-nationals embedded in industry structures of their host countries?

In this SKIN application, the effects of the presence and embeddedness of multi-national enterprises (MNE) in networks of innovation are investigated (Ahrweiler, Schilperoord, Gilbert, and Pyka, 2012). By looking at knowledge flows and capital stocks, the study aimed at investigating whether the mere presence of MNE is beneficial for innovation networks and whether there is an additional advantage if these MNE are engaged in collaborative R&D with other players in the network. The role of MNE for innovation networks was analysed from the perspective of their subsidiaries´ host countries. The simulation was grounded in the empirical example of Ireland, enabling one to analyse the role of MNE in the Irish indigenous industry.

Scenario modelling of the role of MNE for host countries is highly firm relevant: in Ireland, there has been a growth in the high-technology industry sectors, but this has only been fostered by foreign-owned MNE. The MNE were still poorly integrated into Irish networks, clusters and innovation centres.

For the experiments, we operationalised the policy questions in relation to the Irish economy: How important is the knowledge integration function of MNCs as knowledge hubs and financial magnets for regional innovation networks? Does a firm population containing MNCs perform better in terms of knowledge diffusion and innovation performance than a uniform-size population of small and medium firms? What are the effects of MNC presence and activities on the knowledge level of the firm population?

Our results strongly confirmed the current Irish MNC policy strategies. Just attracting and retaining MNCs provides increasing capital availability and innovation performance for the indigenous industry. Surprisingly, even the mere presence of MNCs in the indigenous economy raises the knowledge flows in the host country's industry because firms can more safely engage in R&D and market activities. This is intensified when MNCs engage in local learning activities and embed themselves into the R&D network of regional innovation. The agent-based simulation confirmed that MNCs in R&D collaboration with the indigenous innovation network improve the knowledge and competence level of the whole industry and the innovation diffusion and collaborative arrangements in the host country.

How do entrepreneurs decide on venue and evaluate opportunities for their start-up?

The Irish-funded research programme "Innovation Policy Simulation for the Smart Economy" (IPSE) analysed innovation potentials and innovation strategies in and for Ireland. For example, Ireland currently prioritises its research funding thematically, technologically and sectorally concentrating on areas with high innovation potential. What are the effects and impacts of this strategy? What type of innovation landscape will be created by this prioritisation? Furthermore, in 2013 Ireland established a public-sector–driven centralised technology transfer organisation (cTTO) to work alongside numerous incubators (e.g. NovaUCD) and low-institutionalised tech transfer models. What are the effects and impacts of the different TTO models on innovation performance? Finally, there are only few publicly financed intermediaries between academia and industry such as the Fraunhofer institutes in Germany. What if there were more of these institutions? The IPSE programme investigates these questions using empirically informed simulations (cf. Ahrweiler, Gilbert, and Pyka, 2016).

An important part of the activity was to model entrepreneurship behaviour in Ireland by describing how entrepreneurs discover and evaluate new start-up opportunities. For this, a process was developed following empirical data gathered on the Dublin regional innovation network showing how entrepreneurs create start-ups at fertile locations after testing the viability of the start-up opportunity in general – sometimes in partnership with a technology transfer office and possibly other stakeholders – while being part of a competitive system where they navigate between competitors to survive and even grow in international market environments. The simulation (Schilperoord, 2016) enabled the early identification of high-potential start-ups, tested Irish policy instruments for entrepreneurship and explored the supporting roles of entrepreneurial networks and the decision rules for start-up financing in Ireland.

Utility in managerial practice: summary and outlook

What is the utility of the new methodologies for the future development of innovation management? ABM can shed light into the darkness of the future helping to cope with the challenges of complexity, to understand the dynamics of innovation and to identify potential access points for successful interventions. Simulation results can inform about likely future effects of managerial interventions; some of these effects can be surprising and counter-intuitive. New managerial knowledge is generated: complex contexts are made available and accessible via experimentation. Simulations can help and provide practice how to deal with them.

With the new simulation methodologies, counter-factual analysis is possible: they offer a benchmark, including measurable indicators for impact assessment, appraisal and ex-ante evaluation of managerial interventions. Simulation is a tool for "changing history", that is, testing the impact of past interventions by sensitivity analysis, and for "looking into the future" by exploring what-if questions.

For innovation managers, asking what-if questions (ex-ante evaluation) is an option that is normally not easily available in the management world. They can use scenario modelling as a worksite for their job. Experiments can be used to give an indication of the likely effect of a wide variety of management measures: empirical "un-observables", such as knowledge flows in innovation or learning of agents, can be measured.

However, for reliable results that decision-making can be based on, the evidence must be valid – just a "toy model" without any roots in empirical data will not suffice. A "realistic" ABM such as the one presented earlier gets into contact with empirical data in at least three ways: (i) both quantitative and qualitative empirical data are used to calibrate the model; (ii) data are processed in simulation experiments for producing particular scenarios (sensitivity analyses, ex-ante evaluation); and (iii) the simulations produce artificial data, which need to be analysed and interpreted, and which need to be validated against empirical data.

Simulation models are evaluated and validated by their users (cf. Ahrweiler and Gilbert, 2005, 2015), in this case by innovation managers. To trust the model and its results, they need to understand the mechanisms represented in the model, feel that they have had an input in the design of the agent rules and characteristics and agree that the dynamics of the model are sufficiently close to what they observed had actually happened. As these are relatively new methodologies for practical use, which are not yet part of the regular curricular in international business studies, training and capacity building is required for enabling innovation managers to use agent-based modelling for innovation management simulations.

Note

1 Intelligent"does not necessarily equal, rational", but means that agents display decision-making and strategies for action that have also been observed and analysed by empirical research.

References

Abrahamson, E. and Rosenkopf, L. (1997). Social network effects on the extent of innovation diffusion: a computer simulation. *Organization Science*, 8(3), 289–309.

Ahrweiler, P. (Ed.) (2010). *Innovation in complex social systems*. London: Routledge.

Ahrweiler, P. (2016). Research can be more responsible with the right Partner. *Euroscientist*, January 2016. www.euroscientist.com/research-can-be-more-responsible-with-the-right-partner/.

Ahrweiler, P. (2017a). Agent-based simulation for science, technology, and innovation policy. *Scientometrics*, 110(1), 391–415.

Ahrweiler, P. (2017b). Simulationsexperimente realexperimenteller Politik – der Gewinn der Zukunftsdimension im Computerlabor. In Böschen, S., Gross, M. and Krohn, W. (Eds.), *Experimentelle Gesellschaft*. Nomos Verlagsgesellschaft, edition sigma: Baden-Baden, pp. 199–237.

Ahrweiler, P. and Gilbert, N. (2005). Caffe Nero: the evaluation of social simulation. *Journal of Artificial Societies and Social Simulation*, 8(4).

Ahrweiler, P., Gilbert, N. and Pyka, A. (2004). Simulating knowledge dynamics in innovation networks. In Leombruni, R. and Richiardi, M. (Eds.), *Industry and labor dynamics: the agent-based computational economics approach*. Singapore: World Scientific Press, pp. 284–296.

Ahrweiler, P., Gilbert, N. and Pyka, A. (2006). Institutions matter but . . . organisational alignment in knowledge-based industries. *Science, Technology & Innovation Studies*, 2(1), 39–58.

Ahrweiler, P., Gilbert, N. and Pyka, A. (2011). Agency and structure. A social simulation of knowledge-intensive industries. *Computational & Mathematical Organization Theory (CMOT)*, 17(1), 59–76.

Ahrweiler, P., Gilbert, N. and Pyka, A. (Eds.) (2016). *Joining complexity science and social simulation for innovation policy. Agent-based modelling using the SKIN platform*. Cambridge: Cambridge Scholars Publishing.

Ahrweiler, P., Pyka, A. and Gilbert, N. (2011). A new model for university-industry links in knowledge-based economies. *Journal of Product Innovation Management (JPIM)*, 28, 218–235.

Ahrweiler, P., Pyka, A. and Gilbert, N. (2014). Simulating knowledge dynamics in innovation networks: an introduction. In Gilbert, N., Ahrweiler, P. and Pyka, A. (Eds.), *Simulating knowledge dynamics in innovation networks*. Heidelberg/New York: Springer, pp. 1–14.

Ahrweiler, P., Schilperoord, M., Gilbert, N. and Pyka, A. (2012). Simulating the role of MNCs for knowledge and capital dynamics in networks of innovation. In Heidenreich, M (Ed.), *Innovation and institutional embeddedness of multinational companies*. Edward Elgar: Cheltenham, UK, pp. 141–168.

Ahrweiler, P., Schilperoord, M., Pyka, A. and Gilbert, N. (2015). Modelling research policy – Ex-ante evaluation of complex policy instruments. *Journal of Artificial Societies and Social Simulation (JASSS)*, 18(4), 5.

Ahuja, G. (2000). Collaboration networks, structural holes, and innovation. *Administrative Science Quarterly*, 45, 425–455.

Albert, R. and Barabási, A.-L. (2002). Statistical mechanics of complex networks. *Reviews of Modern Physics T4*, 1, 47–97.

Anderson, P. (1999). Complexity theory and organization science. *Organization Science*, 10(3), 216–232.

Argyris, C. and Schön, D. A. (1996). *Organizational learning: a theory of action perspective*. Reading, MA: Addison-Wesley.

Arthur, B. (1989). Competing technologies, increasing returns, and lock-in by historical events. *Economic Journal*, 99, 116–131.

Arthur, B. (1998). *Increasing returns and path dependence in the economy*. Ann Arbor: University of Michigan Press.

Arthur, W. B. and Polak, W. (2006). The evolution of technology within a simple computer model. *Complexity*, 11(5), 23–31.

Asheim, B. (2010). Innovation is small: SMEs as knowledge explorers and exploiters. In Ahrweiler, P. (Ed.), *Innovation in complex social systems*. London: Routledge, pp. 110–121.

Axelrod, R. M. (1997). *The complexity of cooperation: agent-based models of competition and collaboration*. Princeton: Princeton University Press.

Balke, T. and Gilbert, N. (2014). How do agents make decisions? A survey. *Journal of Artificial Societies and Social Simulation*, 17(4), 13.

Ballot, G. and Taymaz, E. (1997). The dynamics of norms in a micro-to-macro model: the role of training, learning and innovation. *Journal of Evolutionary Economics*, 7, 435–457.

Ballot, G. and Taymaz, E. (1999). Technological change, learning and macro-economic coordination: an evolutionary model. *Journal of Artificial Societies and Social Simulation*, 2. www.soc.surrey.ac.uk/JASSS/2/2/3.html.

Bar-Yam, Y. (1997). *Dynamics of complex systems*. Reading: Addison Wesley.

Bar-Yam, Y. (2004). *Making things work: solving complex problems in a complex world*. Cambridge: Knowledge Press.

Barabási, A-L. and Albert, R. (1999). Emergence of scaling in random networks. *Science*, 286, 509–512.

Barreteau, O. and Le Page, C. (2011). Using social simulation to explore the dynamics at stake in participatory research. *Journal of Artificial Societies and Social Simulation*, April 14.

Bhupatiraju, S., Nomaler, Ö., Triulzi, G. and Verspagen, B. (2012). Knowledge flows – analyzing the core literature of innovation, entrepreneurship and science and technology studies. *Research Policy*, 41(7), 1205–1218.

Birchenhall, C. (1995). Modular technical change and genetic algorithms. *Computational Economics*, 8, 233–253.

Bonabeau, E. (2001). Control mechanisms for distributed autonomous systems: insights from the social insects. In Segal, L. and Cohen, I. R. (Hg.) *Design principles for the immune system and other distributed autonomous systems*. Oxford, pp. 281–292.

Bozeman, B. and Lee, S. (2005). The impact of research collaboration on scientific productivity. *Social Science Studies*, 35(5), 673–702.

Braha, D., Minai, A. and Bar-Yam, Y. (Eds.) (2008). *Complex engineered systems: science meets technology*. New York: Springer.

Broekhuizen, T. L. J., Delre, S. A. and Torres, A. (2011). Simulating the cinema market: how cross-cultural differences in social influence explain box office distributions. *Journal of Product Innovation Management*, 28, 204–217.

Brown, S. L. and Eisenhardt, K. M. (1998). *Competing on the edge: strategy as structured chaos*. Boston, MA: Harvard Business School Press.

Buijs, J. (2003). Modelling product innovation processes, from linear logic to circular chaos. *Creativity & Innovation Management*, 12(2), 76–93.

Burt, R. S. (1992). *Structural holes*. Cambridge, MA: Harvard University Press.

Burt, R. S. (2004). Structural holes and good ideas. *American Journal of Sociology*, 110(2), 349–399.

Cantner, U. and Pyka, A. (1998). Absorbing technological spillovers: simulations in an evolutionary framework. *Industrial and Corporate Change*, 7, 369–397.

Casti, J. (1995). *Complexification. Explaining a paradoxical world through the science of surprise*. New York: Harper Collins.

Chesbrough, H. (2003). *Open innovation: the new Imperative for creating and profiting from Technology*. Boston, MA: Harvard Business School Press.

Chiaromonte, F. and Dosi, G. (1993). Heterogeneity, competition and macroeconomic dynamics. *Structural Change and Economic Dynamics*, 4, 39–63.

Chiaromonte, F., Dosi, G. and Orsenigo, L. (1993). Innovative learning and institutions in the process of development: on the foundations of growth regimes. In Thompson, R. (Ed.), *Learning and technological change*. Macmillan Press, 117–149.

Chiva-Gomez, R. (2004). Repercussions of complex adaptive systems on product design management. *Technovation*, 24(9), 707–711.

Cooper, B. (2000). Modelling research and development: how do firms solve design problems? *Journal of Evolutionary Economics*, 10, 395–413.

Cowan, R., Jonard, N. and Zimmermann, J.-B. (2007). Bilateral collaboration and the emergence of innovation networks. *Management Science*, 53, 1051–1067.

Cunha, M. P. and Comes, J. E. S. (2003). Order and disorder in product innovation models. *Creativity & Innovation Management*, 12(3), 174–187.

Dawid, H. (2006). Agent – based models of innovation and technological change. In Tesfatsion, L. and K. Judd (Eds.), *Handbook of computational economics II: agent-based computational economics*. North – Holland, pp. 1235–1272.

Dawid, H. and Neugart, M. (2011). Agent-based models for economic policy design. *Eastern Economic Journal*, 37(1), 44–50.

Dawid, H. and Reimann, M. (2003). Diversification: a road to inefficiency in product innovations? CEM Working Paper 2003/63, University of Bielefeld.

Dawid, H. and Reimann, M. (2004). Evaluating market attractiveness: individual incentives vs. industrial profitability, to be published in *Computational Economics*.

Dawid, H., Reimann, M. and Bullnheimer, B. (2001). To innovate or not to innovate? *IEEE Transactions on Evolutionary Computation*, 5, 471–481.

Dooley, K. and van de Ven, A. (1999). Explaining complex organizational dynamics. *Organization Science*, 10(3), 358–372.

Doran, J. and Gilbert, G. N. (1994). Simulating societies: an introduction. In Doran, J. and Gilbert, G. N. (Eds.), *Simulating Societies: the computer simulation of social phenomena*. London.

Dosi, G., Fabiani, S., Aversi, R. and Meacci, M. (1994). The dynamics of international differentiation: a multi-country evolutionary model. *Industrial and Corporate Change*, 3, 225–242.

Dosi, G., Marsili, O., Orsenigo, L. and Salvatore, R. (1995). Learning, market selection and the evolution of industrial structures. *Small Business Economics*, 7, 411–436.

Ebeling, W., Molgedey, L. and Reimann, A. (2000). Stochastic urn models of innovation and search dynamics. *Physica A*, 287, 599–612.

Eisenhardt, K. M. and Bhatia, M. M. (2002). Organizational complexity and computation. In Baum, J. A. C. (Ed.), *Companion to organizations*. Oxford: Blackwell.

Epstein, J.M. and Axtell, R. (1996). *Growing artificial societies: social science from the bottom up*. Cambridge, MA: MIT Press.

European Commission (Ed.) (2009). Directorate-general infso: European commission workshop report: using network analysis to assess systemic impacts of research. Brussels, Belgium.

Fagerberg, J., Fosaas, M. and Sappraser, K. (2012). Innovation: exploring the knowledge base. *Research Policy*, 41(7), 1132–1153.

Fagerberg, J., Mowery, D. and Nelson, R. R. (2006). *The Oxford handbook of innovation*. Oxford: Oxford University Press.

Fagiolo, G. and Dosi, G. (2003). Exploitation, exploration and innovation in a model of endogenous growth with locally interacting agents. *Structural Change and Economic Dynamics*, 14, 237–273.

Flake, G.W. (1999). *The computational beauty of nature*. Cambridge, MA: MIT Press.

Frenken, K. (2001). Fitness landscapes, heuristics and technological paradigms: a critique on random search models in evolutionary economics. In Dubois, D. M. (Ed.), *Computing anticipatory systems* (Vol. 573). Melville, NY: American Institute of Physics, pp. 558–565.

Frenken, K. (2006). *Innovation, evolution and complexity theory*. Cheltenham: Edward Elgar Publishing.

Garcia, R. and Jager, W. (2011). Agent-based modeling of innovation diffusion, special issue. *Journal of Product Innovation Management*, 28(2).

Gell-Mann, M. (1994). *The quark and the Jaguar*. New York: Freeman & Co.

Gilbert, N. (2008). *Agent-based models*. Thousand Oaks, CA: Sage Publications.

Gilbert, N. and Ahrweiler, P. (2009). The epistemologies of social simulation research. In Squazzoni, F. (Ed.), *Epistemological aspects of computer simulation in the social sciences*. Berlin/New York: Springer, pp. 12–28.

Gilbert, N., Ahrweiler, P., Barbrook-Johnson, P., Narasimhan, K. and Wilkinson, H. (2018). Computational modelling of public policy: reflections on practice. *Journal of Artificial Societies and Social Simulation (JASSS)*, 21(1), 14.

Gilbert, N., Ahrweiler, P. and Pyka, A. (2007). Learning in innovation networks – some simulation experiments. *Physica A: Statistical Mechanics and Its Applications*, 378(1) 667–693.

Gilbert, N., Ahrweiler, P. and Pyka, A. (2010). Learning in innovation networks – some simulation experiments. Re-Print. In Ahrweiler, P. (Ed.), *Innovation in complex social systems*. London: Routledge, pp. 235–249.

Gilbert, N. (1997). A simulation of the structure of academic science. *Sociological Research Online*, 2(2). www.socresonline.org.uk/2/2/3.html.

Gilbert, N., Pyka, A. and Ahrweiler, P. (2001). Innovation networks-a simulation approach. *Journal of Artificial Societies and Social Simulation*, 4. www.soc.surrey.ac.uk/JASSS/4/3/8.html.

Gilbert, N. and Troitzsch, K.G. (2005). *Simulation for the social scientist*. (2nd. ed.), Maidenhead: Milton Keynes.

Gloor, P. (2006). *Swarm creativity – competitive advantage through collaborative innovation networks*. Oxford: Oxford University Press.

Grabowski, H. G. and Vernon, J. M. (1987). Pioneers, imitators, and generics ? A simulation model of Schumpeterian competition. *Quarterly Journal of Economics*, 102, 491–525.

Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology*, 78(6), 1360–1380.

Heidenreich, M., Barmeyer, C. and Koschatzky, K. (2010). Product development in multinational companies: the limits for the internationalization of R&D projects. In Ahrweiler, P. (Ed.), *Innovation in complex social systems*. London: Routledge, pp. 137–149.

Holland, J. H. (1995). *Hidden order: how adaptation builds complexity*. Reading, MA: Addison-Wesley.

Kauffman, S. (1995). *At home in the universe. The search for laws of self-organization and complexity*. Oxford: Oxford University Press.

Kauffman, S. A. (1993). *The origins of order: self-organization and selection in evolution*. New York: Oxford University Press.

Klepper, S. (1996). Entry, exit, growth, and innovation over the product life cycle. *American Economic Review*, 86, 562–583.

Korber, M. and Paier, M. (2014). Simulating the effects of public funding on research in life sciences: direct research funds versus tex incentives. In Gilbert, N., Ahrweiler, P. and Pyka, A. (Eds.), *Simulating knowledge dynamics in innovation networks*. Heidelberg/New York: Springer, pp. 99–130.

Knight, F. H. (1921). *Risk, uncertainty and profit*. Boston, MA: Hart, Schaffner & Marx.

Kwasnicki, W. (2001). Firms decision making process in an evolutionary model of industrial dynamics. *Advances in Complex Systems*, 1, 1–25.

Lane, D., van der Leeuw, S., Pumain, D. and West, G. (Eds.) (2009). *Complexity perspectives in innovation and social change*. Berlin/New York: Springer.

Lazer, D. and Friedman, A. (2007). The network structure of exploration and exploitation. *Administrative Science Quarterly*, 52(4), 667–694.

Lindgren, K. (1992). *Evolutionary phenomena in simple dynamics. Vol. 10*. Reading: Addison-Wesley.

Llerena, P. and Oltra, V. (2002). Diversity of innovative strategy as a source of technological performance. *Structural Change and Economic Dynamics*, 13, 179–201.

Loasby, B. J. (1999). *Knowledge, institutions and evolution in economics*. London: Routledge.

Macal, Ch. M. and North, M.J. (2009). Agent-based modeling and simulation. In Rossetti, M.D., Hill, R.R., Johansson, B., Dunkin, A. and Ingalls, R.G. (Hg.) *Proceedings of the 2009 Winter Simulation Conference*. Austin, TX, 86–98.

Malerba, F., Nelson, R., Orsenigo, L. and Winter, S. (1999). 'History-friendly' models of industry evolution: the computer industry. *Industrial and Corporate Change*, 8, 3–40.

Malerba, F., Nelson, R., Orsenigo, L. and Winter, S. (2001). Competition and industrial policies in a 'history-friendly' model of the evolution of the computer industry. *International Journal of Industrial Organization*, 19, 635–664.

Malerba, F. and Orsenigo, L. (2002). Innovation and market structure in the dynamics of the pharmaceutical industry and biotechnology: towards a history-friendly model. *Industrial and Corporate Change*, 11, 667–703.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2(1), 71–87.

March, J. G. and Olsen, J. P. (1975). The uncertainty of the past: organizational learning under ambiguity. *European Journal of Political Research*, 3, 147–171.

Martin, B. R. (2012). The evolution of science policy and innovation studies. *Research Policy*, 41(7), 1219–1239.

McKelvey, B. (1999). Self-organization, complexity, catastrophe, and microstate models at the edge of chaos. In Baum, J. A. C. and McKelvey, B. (Eds.), *Variations in organization science – in honor of Donald T. Campbell*. Thousand Oaks, CA: Sage Publications.

Meagher, K. and Rogers, M. (2004). Network density and R&D spillovers. *Journal of Economic Behavior and Organization*, 53, 237–260.

Narula, R. and Michel, J. (2010). Reverse knowledge transfer and its implications for European policy. In Ahrweiler, P. (Ed.), *Innovation in complex social systems*. London: Routledge, pp. 122–136.

Natter, M., Mild, A., Feuerstein, M., Dorffner, G. and Taudes, A. (2001). The effect of incentive schemes and organizational arrangements on the new product development process. *Management Science*, 47, 1029–1045.

Newman, M. (2003). The structure and function of complex networks. *SIAM Review*, 45, 167–256.

North, M. J. and Macal, C. M. (2007). *Managing business complexity: discovering strategic solutions with agent-based modeling and simulation*. Oxford: Oxford University Press.

Porter, K. A., Bunker Whittington, K. C. and Powell, W. W. (2005). The institutional embeddedness of high-tech regions: relational foundations of the Boston biotechnology community. In Breschi, S. and Malerba, F. (Eds.), *Clusters, networks, and innovation*, Oxford: Oxford University Press.

Powell, W. W., White, D. R., Koput, K. W. and Owen-Smith, J. (2005). Network dynamics and field evolution: the growth of inter-organizational collaboration in the life sciences. *American Journal of Sociology*, 110(4), 1132–1205.

Prigogine, I. and Stengers, I. (1984). *Order out of chaos*. New York: Bantam Books.

Pyka, A. and Cantner, U. (1998). Absorbing technological spillovers: simulations in an evolutionary framework. *Industrial and Corporate Change*, 7(2), 369–397.

Pyka, A. and Kueppers, G. (Eds.) (2003). *Innovation networks. Theory and practice*. Cheltenham: Edward Elgar Publishing.

Pyka, A. and Fagiolo, G. (2005). Agent-based modelling: a methodology for neo-Schumpeterian economics. In Hanusch, H. and Pyka, A. (Eds.), *The Elgar companion to neo-Schumpeterian economics*. Cheltenham: Edward Elgar Publishing.

Pyka, A., Gilbert, N. and Ahrweiler, P. (2007). Simulating knowledge generation and distribution processes in innovation collaborations and networks. *Cybernetics and Systems*, 38(7), 667–693.

Pyka, A. and Ahrweiler, P. (2008). Innovation networks – an introduction. *International Journal of Foresight and Innovation Policy*, 4(3/4), 1–8.

Pyka, A., Ahrweiler, P. and Gilbert, N. (2009). Agent-based modelling of innovation networks – the fairy tale of spillovers. In Pyka, A. and Scharnhorst, A. (Eds.), *Innovation networks. New approaches in modeling and analyzing*. Berlin/New York: Springer, pp. 101–126.

Rodan, S. (2005). Exploration and exploitation revisited: extending March's model of mutual learning. *Scandinavian Journal of Management*, 21(4), 407–428.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). New York: Free Press.

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, 1, 143–186.

Schilling, M. A. and Phelps, C. C. (2005). Interfirm collaboration networks: the impact of small world connectivity on firm innovation. *Management Science*, 53(7), 1113–1126.

Schilperoord, M. (2016). Start-ups when and where? Using the SKIN platform for modelling the birth of new firms. In Ahrweiler, P., Gilbert, N. and Pyka, A. (Eds.), *Joining complexity science and social simulation for innovation policy. Agent-based modelling using the SKIN platform*. Cambridge Scholars Publishing, pp. 326–348.

Schumpeter, J. (1912). *The theory of economic development*. Oxford: Oxford University Press.

Siegel, D. S., Waldman, D., Atwater, L. and Link, A. N. (2003). Commercial knowledge transfers from universities to firms: improving the effectiveness of university-industry collaboration. *Journal of High Technology Management Research*, 14, 111–133.

Silverberg, G. and Verspagen, B. (1994). Collective learning, innovation and growth in a boundedly rational, evolutionary world. *Journal of Evolutionary Economics*, 4, 207–226.

Silverberg, G. and Verspagen, B. (1995). An evolutionary model of long term cyclical variations of catching up and falling behind. *Journal of Evolutionary Economics*, 5, 209–227.

Silverberg, G. and Verspagen, B. (1996). From the artificial to the endogenous: modeling evolutionary adaptation and economic growth. In Helmstädter, E. and Perlman, M. (Eds.), *Behavioral norms, technological progress, and economic dynamics*. Ann Arbor: The University of Michigan Press.

Silverberg, G. and Verspagen, B. (2005). A percolation model of innovation in complex technology spaces. *Journal of Economic Dynamics & Control*, 29(1–2), 225–244.

Silverberg, G. and Verspagen, B. (2007). Self-organization of R&D search in complex technology spaces. *Journal of Economic Interaction and Coordination*, 2(2), 195–210.

Sorenson, O., Rivkin, J. and Fleming, L. (2006). Complexity, networks and knowledge flow. *Research Policy*, 35(7), 994–1017.

Smith, H. L. and Ho, K. (2006). Measuring the performance of Oxford University, Oxford Brookes University and the government laboratories' spin-off companies. *Research Policy*, 35, 1554–1568.

Stewart, I. (1989). *Does God play dice? The mathematics of chaos*. Cambridge, MA: Blackwell.

Tesfatsion, L. (2003). Agent-based computational economics. Economics Working Papers (2002–2016). Iowa State University.

Tesfatsion, L. (2006). Agent-based computational economics: a constructive approach to economic theory. In Tesfatsion, L. and Judd, K. (Eds.), *Handbook of computational economics II: agent-based computational economics*. North–Holland, Elsevier.

Thursby, J. and Kemp, S. (2002). Growth and productive efficiency of university intellectual property licensing. *Research Policy*, 31, 109–124.

Uzzi, B. (1997). Social structure and competition in inter-firm networks: the paradox of embeddedness. *Administrative Science Quarterly*, 42, 35–67.

Valente, T. W. (1996). *Network models of the diffusion of innovations*. Cresskill: Hampton Press.

Verspagen, B. and Duysters, G. (2004). The small worlds of strategic technology alliances. *Technovation*, 24, 563–571.

Von Hippel, E. (2006). *Democratizing innovation*. Cambridge, MA: MIT Press.

Waldrop, M. M. (1992). *Complexity: the emerging science at the edge of order and chaos*. New York: Simon & Schuster.

Walker, G., Kogut, B. and Shan, W. (1997). Social capital, structural holes and the formation of an industry network. *Organization Science*, 8, 108–125.

Wasserman, S. and Faust, K. (1994). *Social network analysis: methods and applications*. Cambridge: Cambridge University Press.

Watts, D. (1999). *Small worlds*. Princeton: Princeton University Press.

Watts, D. and Strogatz, S. (1998). Collective dynamics of 'small-world' networks. *Nature*, 393, 440–442.

Watts, C. and Gilbert, N. (2014). *Simulating innovation. Computer-based tools for rethinking innovation*. Cheltenham: Edward Elgar Publishing.

Windrum, P. (2007). Neo-Schumpeterian simulation models. In Hanusch, H. and Pyka, A. (Eds.), *The Edward Elgar companion to Neo-Schumpeterian economics*. Cheltenham: Edward Elgar Publishing, 405–439.

Windrum, P. and Birchenhall, C. (1998). Is product life cycle theory a special case? dominant designs and the emergence of market niches through coevolutionary-learning. *Structural Change and Economic Dynamics*, 9, 109–134.

Winter, S. G., Kaniowski, Y. M. and G. Dosi (2000). Modelling industrial dynamics with innovative entrants. *Structural Change and Economic Dynamics*, 11(3), 255–293.

Winter, S. G., Kaniowski, Y. M. and G. Dosi (2003). A baseline model of industry evolution. *Journal of Evolutionary Economics* 13(4), 355–383.

Wooldridge, M. (2000). *Reasoning about rational agents*. Cambridge, MA: MIT Press.

Yildizoglu, M. (2001). Connecting adaptive behavior and expectations in models of innovation: the potential role of artificial neural networks. *European Journal of Economic and Social Systems*, 15, 203–220.

Zhang, T., Gensler, S. and Garcia, R. (2011). A study of the diffusion of alternative fuel vehicles: an agent-based modeling approach. *Journal of Product Innovation Management*, 28, 152–168.

Zhang, T. and Nuttall, W. J. (2011). Evaluating government's policies on promoting smart metering diffusion in retail electricity markets via agent-based simulation. *Journal of Product Innovation Management*, 28, 169–186.